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Consulting Project for Banco Invest:

Development of Internal Rating Model

Limitations of the Report and Recommendations for the Bank

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Abstract

The group work to which this individual report should be attached does not mention certain characteristics of the data that could be used for other research papers and for the bank. As such, this individual work develops the topics of limitations of the database used, the limitations of the type of work done in the Portuguese market, key characteristics of the variables used, and recommendations to the bank on further improvement of the model used and, from the perspective of a consultant, on what the bank could improve internally.

Keywords: Credit Risk, Limitations, Recommendations, Logit Model

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1 Introduction

In this part, the topics of limitations and recommendations will be developed, or more specifically, the limitations of the database used and the companies analysed to create the model in the report, and possible recommendations for the bank to further improve the said model.

2 Limitations and Recommendations

2.1 Limitations

First and foremost, it is important to stress out that, as explained in the methodology part of the report, the logit model applied is consistent with financial theory. As such, the limitations here explored do not invalidate the results achieved in the report, they merely show that those results could be better if it were not for the limitations here presented.

Sabi database lacked consistency in some values, which forced us to present a model without variables related to coverage. As shown in the literature presented in the report, the best variables to predict default events are related to liquidity, profitability, leverage, coverage and activity. A better model should strive to have at least one variable representing coverage. Finally, the variable presented in the report as non-accounting (age), although not common in the models defended by Altman, more financial focused, does appear in other models and helps the validation of the model presented in the report.

The bankruptcies presented in the dataset represent only bankruptcies (the act of a company declaring itself bankrupt). They do not represent other default events (for example, the company defaulting on a single interest payment). Data related to such events is scarce, but if it were used, it would reinforce the results achieved in the group report since, in theory, companies who default more should have a higher probability of going bankrupt. Also related to this topic, if our model

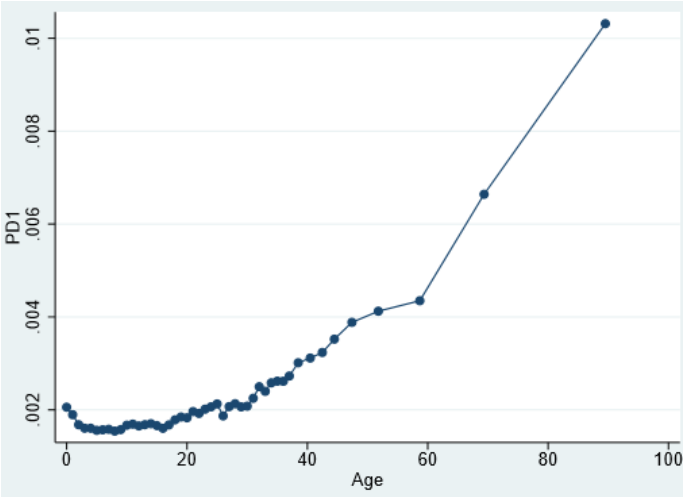
analysed default events, then variables related to liquidity should have more importance, since companies with higher liquidity constraints should be more prone to default on their payments.

Another important limitation comes regarding capital markets. Some models analyse changes in the stock price or volatility to predict default events. This is simply not possible to do for the Portuguese market, since at the time of writing of this report, there are less than fifty companies traded regularly in the Portuguese stock exchange. For comparison, our dataset has more than 50000 companies.

Regarding the seven variables used in the model (Age, NI/TA, OR/TA, Eq/TA, Cash/TA, WC/TA, AR/S), some show an interesting behaviour, which on the report is considered an outlier, but which could be useful to analyze on other papers more focused on each. The graphs presented below show the relation between PD1 (probability of default in one year) and the respective variable (each dot represents a one percent percentile of the respective variable).

Age, as hypothesized in the report, should be positive, since older companies should be prone to default. We see that in Figure 1, however, for younger companies, with less than two years, the relation seems to be inverse. Young companies are more likely to default in their first months. Although not the topic of the report, some of the papers mentioned do show similar results. Due to the minimum size of a million in assets, companies with less than two years of age are a very small percentage of the dataset (it is rare for companies with just two years of life to reach a million in assets), and therefore considered an outlier.

Figure 1 - Age



NI/TA and Eq/TA behave as expected without any meaningful outliers. The only point worth mentioning is that for negative values the PD increases exponentially, but for a positive value the PD comes close to 0, with little marginal effect.

Figure 2 - NI/TA

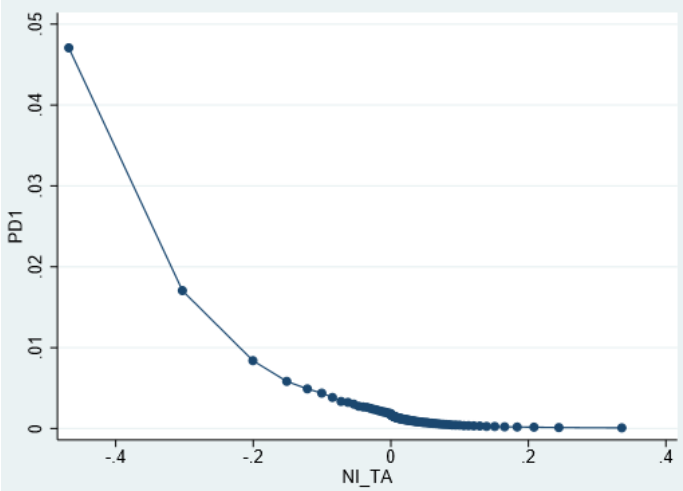
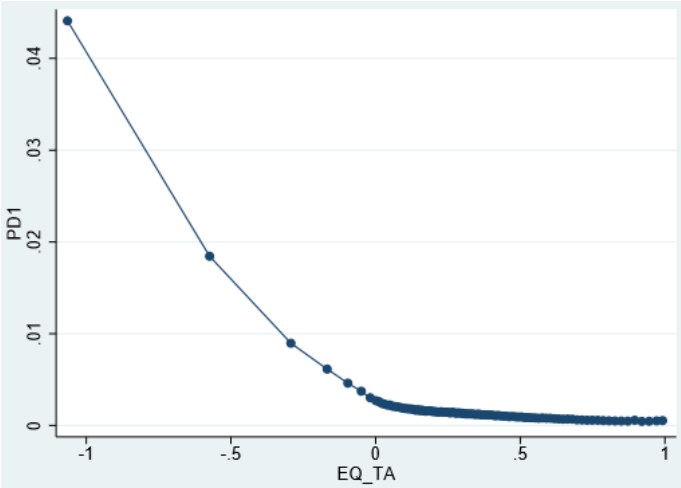
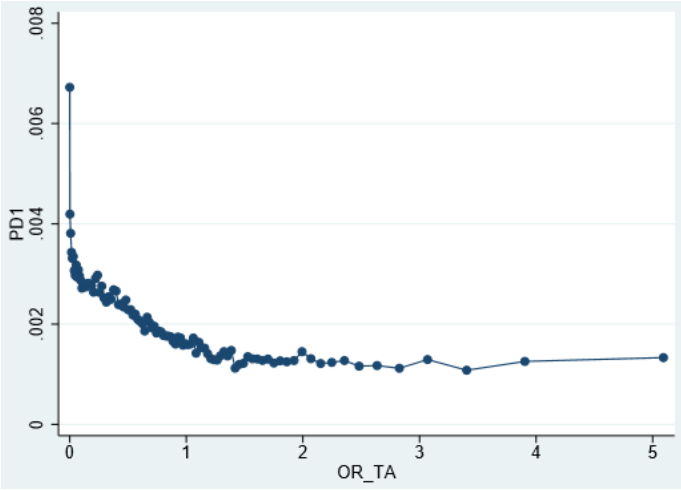


Figure 3 - EQ/TA



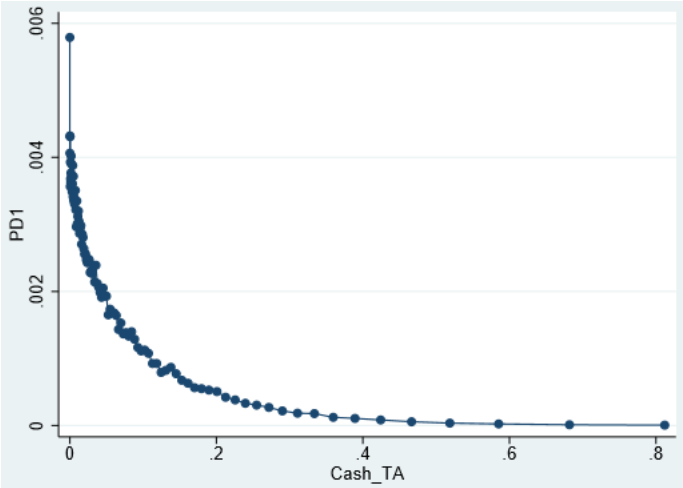
The variable OR/TA shows three different behaviours. The first, for an OR/TA bellow 0.25, shows an exponential decrease in the PD as the variable increases. The second, between 0.25 and 1.5, has a more linear behaviour, where a higher OR/TA means a lower PD. The third and last is for an OR/TA larger than 1.5, where there is no change in the PD the more OR/TA grows. In other words, after 1.5, increases in OR/TA have no effect whatsoever on the PD. This could be explained due to the fact that an OR/TA higher than 1.5 is huge, something extremely hard to keep in the long run and potentially a single year outlier (a lucky year).

Figure 4 - OR/TA



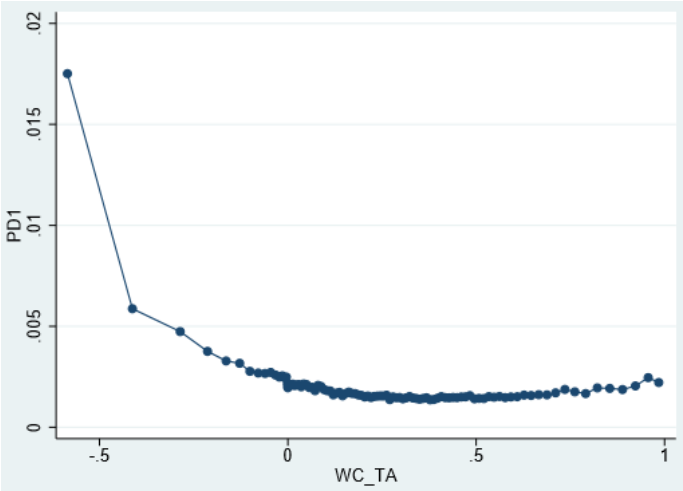
Cash/TA has a behaviour like OR/TA. The first stage, from 0 to 0.05, has an exponential behaviour (little to no cash can be disastrous for a company). The second stage, from 0.05 to 0.4, has a somewhat linear behaviour. The third and last stage, between 0.4 and 1, shows very little change in PD, close to 0, which shows how unlikely it is for a company with a lot of cash to go bankrupt next year.

Figure 5 - Cash/TA



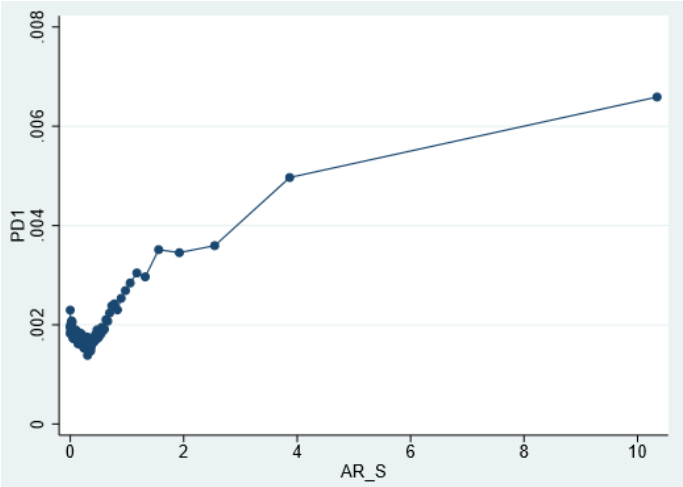
WC/TA shows a clear difference for negative and positive values. Negative values increase the PD. Positive values have almost no effect on the PD. However, for very high WC/TA values, the PD starts to slightly increase. This might be explained because companies with a WC/TA too high might be allocating their capital poorly. It is good for a company to have liquidity, which is what this variable represents, but too much liquidity can be bad, in the sense that the company is being too conservative and not allocating its capital properly.

Figure 6 - WC/TA



AR/S shows two different behaviours. The first one goes against the hypothesis, where for values between 0 and 0.5, an increase in the AR/S leads to a lower PD. The second one shows what was expected, higher AR/S means higher PD. The explanation for this is simple. A high value for AR/S means that the company depends too much on credit from its customers, that it takes more time for sales to be converted in cash, which puts the company in a riskier position. But AR (accounts receivable) is still an asset, meaning that a higher value should be positive for the company. The conclusion is that for low values (below 0.5) the company does not rely too heavily on its costumers fulfilling their obligations, but for higher values the dependency on credit is too much, showing a likelier possibility of those AR never truly converting into cash.

Figure 7 - AR/S



2.2 Recommendations

Finally, the recommendations to the Bank, most of which are on how to avoid some of the limitations presented above and on how to best use the model provided.

The entire dataset, as already pointed out, is solely of Portuguese companies. As such, the Bank should only use the model to value Portuguese companies. The model is adjusted for the Portuguese market and it would not make sense to used it to analyze companies on different markets. Different markets have different environments, enough to make some variables have different importance. As such, if the Bank desires to analyze other markets, the Spanish for example, they should rebuild the model but using a dataset of only Spanish companies.

Finally, again, the main limitation, that ends up leading to all the limitations referred before, comes from the lack of proper data. The Bank has much to gain from attempting to collect said data for Portugal. They can do this by keeping records of former companies to whom they lent, who might have defaulted at some point, or even gone bankrupt. The group found this type of data to be strongly lacking in Portugal, only owned by private entities who refuse to share it (like the Bank of Portugal). In a way, the lack of such data shows an opportunity, that if exploited

could give some competitive advantage to the Bank over its competitors and allow for higher income.

3 Conclusion

First, the database used lacked on some values that could improve the model used. This is not a problem on the database itself, but more of a general problem of lack of data for the Portuguese market. Second, some of the variables used present interesting behaviours, whose analysis would only be relevant for other models more focused on specific market segments and individual variables. Third, the Bank should consider potential gains from keeping a record of previous bankruptcies and defaults, and of creating themselves a private database. Finally, this limitations and recommendations serve as indications on what could make the model developed better, but in no way do they invalidate the work done, which is by all accounts, valid and trustworthy.